# CHAPTER 4

# Uncertainty

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## Introduction

The treatment of uncertainty is key to ensuring and maintaining an appropriate level of public safety while allowing the flexibility necessary to reduce costs. This is true for all fire safety engineering calculations whether conducted to meet a performance-based code, to aid in the establishment of a prescriptive requirement, or to compare a performance option to its prescriptive counterpart. However, at present, no method exists for the treatment of uncertainly in a fire safety engineering calculation. Proper treatment of uncertainty will assist engineers and architects in the design process, and assist code officials by increasing confidence in the acceptance of a performance calculation. It will aid researchers in prioritizing enhancements to both the physics and structure of fire models, and aid policymakers by incorporating scientific knowledge and technical predictive abilities in policy decisions.

This chapter is made up of several sections. The first section, Understanding Uncertainty, covers basic concepts of uncertainty and variability in order to develop a common language for discussion among fire safety professionals. It then presents motivating examples that show the importance of dealing with uncertainty in the application of our scientific tools. It is shown how variations in analysis parameters, assumptions, or model inputs can lead to changes in the acceptability of a fire safety design. This is termed *switchover.*[1] A taxonomy is presented in this section that is useful as a framework for understanding, identifying, and investigating uncertainties.

Another section, Treatment of Uncertainty in Design Calculations, discusses the treatment of uncertainty with safety factors as well as quantitative techniques for the treatment of uncertainty in fire protection design calculations. The use of safety factors in both prescriptive and performance-based codes is discussed. Guidance is given on selecting an appropriate factor of safety and on combining safety factors. Quantitative techniques are presented for the treatment of uncertainties in measurement; in analysis parameters, assumptions, and values; and in complex fire models.

A methodology for the application of an uncertainty analysis to a fire safety engineering calculation is suggested. It is shown how results of this type of analysis are used to create distributions of time to untenability, to demonstrate the effect of selecting various sets of performance criteria, to compare two designs, and to provide insight to model development.

The last section of this chapter, Treatment of Uncertainty in Cost-Benefit and Decision Analysis Models, discusses the application of uncertainty analysis to cost-benefit and decision analysis models. An example of a cost-benefit model that incorporates uncertainty is provided.

## Understanding Uncertainty

Uncertainty is a broad and general term used to describe a variety of concepts including but not limited to lack of knowledge, variability, randomness, indeterminacy, judgment, approximation, linguistic imprecision, error, and significance. These and many other facets of uncertainty are discussed in more detail in Chapter 4 of the book *Uncertainty.*[1] The variety of types and sources of uncertainty, along with the absence of agreed-upon terminology, generates considerable confusion in the fire protection engineering world. Many facets of uncertainty can be understood through statistical and scientific concepts, some of which are presented below. However, uncertainties in the engineering design process, such as those surrounding the selection of performance criteria, are best understood by their ability to change the accept-

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ability of a design. Finally, to fully understand uncertainty in fire safety engineering, one must be cognizant of the difficulties in conducting a complete uncertainty analysis.

## Nature and Sources of Uncertainty

Uncertainty is often discussed as though it was synonymous with measurement uncertainty, that is, doubt about the validity of the result of a measurement. Measurement uncertainties are characterized from both a statistical analysis of a series of observations (to determine the random error) and from systematic effects associated with corrections and reference standards (to determine the systematic error). The total error is defined as a combination of random and systematic errors. Much work has been done to reach an international consensus on the evaluation and expression of measurement uncertainty. General rules for evaluating and expressing uncertainty in measurement are provided in a guide published by the American National Standards Institute and the National Conference of Standards Laboratories.[2] An example of dealing with measurement uncertainty in fire protection engineering is found in a study of the uncertainty surrounding the use of thermocouples to measure temperature.[3]

However, uncertainty also arises from a variety of other sources to which standard techniques for the evaluation and expression of uncertainty do not always apply. Uncertainty can arise from a lack of complete knowledge. What is the heat release rate or radiative fraction of a mixed-fuel package? We have not measured and cannot reliably predict the value of these quantities for all potential fuel packages. Furthermore, the heat-release rate and radiative fraction vary with parameters such as geometry, source and strength of ignition, and ventilation conditions. Uncertainty may arise from *randomness,* such as where and how the fire will start. Uncertainty may arise from *indeterminacy,* defined as the inability to know what will happen in the future. For example, building occupancy and furnishings may differ 10 or 20 years after they were first constructed. Uncertainty may arise due to the unpredictability of human behavior. It is unknown what actions each occupant will take upon discovering a fire or hearing an alarm. Uncertainty can arise because of disagreement between information sources. Rates of generation of products of combustion per gram of fuel burned vary from study to study and even from test to test in the same study using the same instruments.

Uncertainty may arise from difficulties in defining the problem. For example, a goal may be established to provide an equivalent level of fire safety. However, equivalency may be defined as providing the same time available for egress, providing the same level of property protection, providing the same level of fire safety for fire fighters entering the building, or all of the above. Uncertainty may also arise from *linguistic imprecision.* It is difficult to determine exactly what is meant by "flame spread should be limited." Uncertainty often refers to *variability,* for example, the ambient temperature and the total number of deaths from fire. These quantities vary in time by season, month, and day. They also vary in space by region of the country and community size. Even if we had complete information, we may be uncertain because of simplifications and approximations introduced due to computational limitations.

There are also important questions related to understanding uncertainties in perceptions, attitudes, and values toward risk. "In addition to being uncertain about what exists in the external world, we may be uncertain about individual preferences, uncertain about decisions relating to potential solutions, and even uncertain about the level and significance of our uncertainty."[1] Uncertainties inherent in the performance-based analysis and design process are discussed in *Introduction to Performance-Based Fire Safety.*[4]

Understanding the level and significance of our uncertainty is crucial to making good fire safety design decisions. It is therefore important that the fire protection engineering community understands basic concepts of probability and statistics, and that the community agrees on terminology for use in discussing uncertainty.

## Terminology for Probability and Statistics

The mathematical concept of probability is used to quantify uncertainty, Elements of probability allow us to quantify the strength of, or confidence in, our conclusions. There are two views of probability, the frequentist (or classical) and the subjectivist (or Bayesian). Each of these are useful in quantifying uncertainties in fire protection engineering. Likewise, inferential statistics has produced an enormous number of analytical tools that allow the engineer or scientist to better understand the systems that generate data. Inferential statistics allows us to go beyond merely reporting data, and enables the drawing of conclusions about the scientific system. Concepts essential to the understanding of uncertainty such as distribution, mean, standard deviation, errors, corrections, correlation, and independence are presented in Section 1 of this handbook. **A** full treatment of probability concepts is presented in Section 1, Chapter 11, and concepts of statistical analysis are presented in Section 1, Chapter 12.

**Probability/frequentist** view: The probability of an event's occurring in a particular scenario is defined as the frequency with which it occurred in a long sequence of similar trials. For example, the probability of a fire pump failure may be defined by failure data for that pump in many fires.

**Probability/Bayesian** view: The probability of an event is the degree of belief that a person has that it will occur, given all relevant information currently known to that person. For example, the probability that a new fire detector will save lives may be based on the judgment of an expert in both fire detection and the nature of fire deaths (who may or may not have frequency data to support such a belief in the classical sense).

Random error and statistical variation: No measurement of an empirical quantity such as the burning rate of jet fuel can be absolutely exact. Imperfections in the measuring instruments and observational technique will inevitably give rise to variations from one observation to the next. The resulting uncertainty depends on the size of the variations between observations and the number of observations taken. Classical, statistical techniques such as standard deviation, confidence intervals, and others can be used to quantify this uncertainty.

**Aleatory uncertainty:** Aleatory uncertainty is due to random variations and chance outcomes and has also been referred to as *randomness*,[5] as *stochastic uncertainty*,[6] and as *statistical uncertainty*.[7] In principle, aleatory uncertainty cannot be reduced but can be better characterized through exhaustive study. Stochastic uncertainty has been defined as "the totality of occurrences that can take place in the particular universe under consideration together with a probabilistic characterization of the likelihood of these occurrences."[8]

**Epistemic uncertainty:** Epistemic uncertainty arises because of lack of knowledge. It has also been referred to as *imprecision*,[5] as *knowledge uncertainty*,[6] as *engineering uncertainty*,[7] and as *subjective uncertainty* because expert judgment is often needed to represent the uncertainty when full knowledge is lacking. In principle, epistemic uncertainty can be reduced through gaining additional information or data. It has been stated that this type of uncertainty often arises due to the uncertainty on the part of the analyst as to how the appropriate values of the quantities should be assigned.[8]

**Scientific versus statistical significance:** *Statistically significant* refers to a mathematical calculation that verifies that two quantities are likely to be the same or different. *Scientifically significant* refers to whether the difference is large enough to be important.

## Uncertainties in the Design Process and the Problem of Switchover

Of practical significance is that direct measurement of the fire safety performance of a building or building system is not usually possible; therefore, we must rely on the technical predictive ability of scientific tools, such as existing fire models. The problem is that the numerous uncertainties in the application of these fire safety design tools often go unrecognized or ignored. Many of these uncertainties are inherent in the design process itself. Variations in analysis parameters, assumptions, or model inputs may cause output criteria to change. *Switchover* occurs when outcome criteria change enough so as to cause a change in the design decision (e.g., the acceptability of a final design). It is critical to know if different sets of reasonable inputs, scenarios, or parameters used in a fire safety engineering design have potential to cause switchover and lead to different acceptable designs.

The Society of Fire Protection Engineers (SFPE) *Engineering Guide to Performance-Based Fire Protection Analysis and Design of Buildings* details several steps in the design process.[9] These are shown in Figure 5-4.1, adapted from the SFPE engineering guide. The stated intent of the guide is to "provide guidance that can be used by both design engineers and approving authorities as a means to

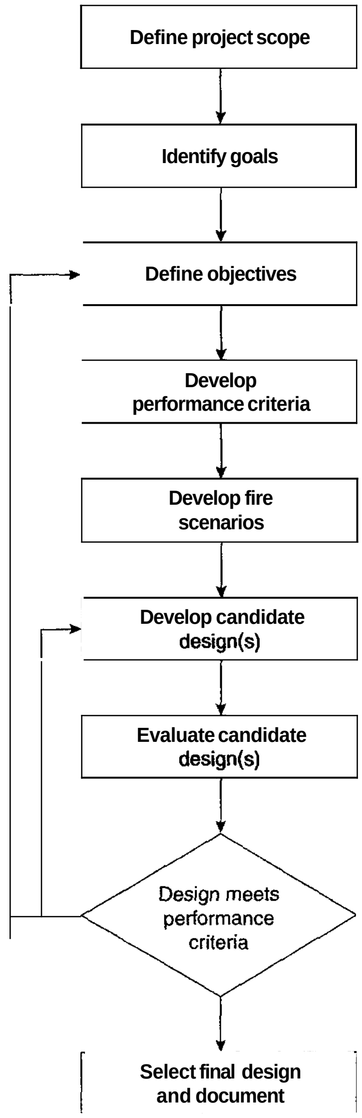


**Figure 5-4.1.** ***Overview of the performance-based design process.***[9]

determine and *document achievement of agreed upon levels of fire safety* for a particular project" (emphasis added).

A review and analysis of the performance-based design process for fire safety engineering outlined in the guide along with a review of several case studies of performance-based, fire safety engineering designs for actual buildings was conducted.[10] This review uncovered seven major barriers to determining and documenting achievement of agreed-upon levels of fire safety for a particular project. All seven barriers involve various types of uncertainty. Thus, there is a well-defined and strong role for uncertainty analysis in improving the ability to document achievement of agreed-upon levels of fire safety. The seven barriers identified are presented below along with a discussion of how they might lead to switchover of a design from acceptable to unacceptable.

**1.** Performance criteria are not established or no agreement exists: There is uncertainty in the selection of performance criteria. In fact, performance criteria have not been established or agreed upon by the fire safety community, and current policy allows the stakeholders themselves to select the criteria to be used for each design. Discussions occur around questions such as the following: Is the set of performance criteria sufficient? What do the numerical values actually represent? Should different criteria be used for different subpopulations, such as for people who are sick, elderly, or have disabilities? At one recent international conference, two engineers presented their performance-based case studies conducted for real clients on actual buildings. They had each followed the current design guidelines; however, they had selected very different performance criteria.[11,12] Differences existed on three levels: (1) the parameters included in the set of performance criteria, (2) numerical values selected as the critical or cut-off values for these parameters, and (3) the presence or absence of a time element for reaching the cut-off values. Since predictions of fire models are compared to selected performance/life safety criteria in order to determine if a design is acceptable, variations in criteria can cause the same design to pass or fail.

**2.** The design fire selection process is unspecified: Design fires are descriptions of fire events (e.g., a grease fire on the stove, a smoldering cigarette fire on the sofa). Along with design fires, several fire scenarios, or descriptions of possible fires that could occur, are developed. For each design fire evaluated, the goal is to provide a fire safety design that would mitigate unwanted fires from developing.

Since it is impossible to evaluate physically the performance of building systems in response to all design fires that might occur, one does not have confidence that design fires and the resulting fire scenarios chosen adequately represent the range of fires that might occur in the building. Usually a designer will try to select worst-case or reasonable worst-case scenarios.* However, it is not always intuitive which scenarios present a worst-case situation or how likely (or unlikely) a particular scenario is. It is debatable whether we should be designing for the one-in-a-million fire and how many design fires and fire scenarios are sufficient. A methodology is needed that would incorporate the likelihood of a design fire and/or associated design fire scenario. It is easy to see how the same design may be deemed acceptable if based on a limited number and type of design fires, or deemed unacceptable if based on an expanded set of scenarios or a different set of scenarios.

**3.** Assumptions are made about human behaviors during fire: During several critical steps in the design process, assumptions are made about human behaviors during fire. For example, some egress models used by fire protection engineers to predict the time required for safely evacuating a building (or part of a building) make many assumptions about how humans behave. Two assumptions are stated in one internationally used egress model: (1) 100 percent of the occupants are readily mobile and (2) occupants begin leaving the building immediately upon hearing an alarm.[13] Experience demonstrates that this is often not the case.[14,15]

Other behavior assumptions may not be explicitly stated but can be inferred from an analysis of model outputs. For example, results from a recently published study of a performance calculation using the egress model in FASTlite reveal that assumptions are made about human behavior during fires.[13] A decrease in the number of exits by one-third increases the egress time by exactly one-third. This suggests an implied assumption that an equal number of people egress through each available exit. More typically, actual human behavior will be to exit following the path one normally uses to enter and exit the building. Existing egress calculations and models need to be evaluated so that unrecognized and/or unstated uncertainties resulting from assumptions regarding human behavior can be identified. Once revealed, the implications of these assumptions need to be explored quantitatively.

4. Predictive fire models have limitations that are not well documented or widely understood: Fire models and other calculation methodologies are often inappropriately used to develop and evaluate trial designs for buildings and/or scenarios outside of the predictive capabilities of the models. This occurs because limitations of fire models are not well documented or widely understood. For example, computer fire models don't model fire directly and only predict fire effects based on user-selected input data. Because many existing fire model and calculation methodologies were originally developed as research tools, model conditions, defined as "fundamental requirements for the model's validity,"[16] are often unknown or unstated. Estimates provided by a model are technically credible only when model conditions have not been violated.

5. Outputs of fire models are point values that do **not** directly incorporate uncertainty: Even when the model is used within its intended limitations, fire model outputs are point values that do not reflect inherent input uncertainties (e.g., fire growth rates, initial conditions). Without knowledge of the uncertainty surrounding a prediction, it is impossible to be certain of a design's acceptability. One example is modeling the response of fire protection equipment such as sprinklers, heat detectors, and smoke detectors. Predictions of the time to activation of such devices would specify, for example, 121 s. However, the actual time to activation may be higher or lower depending on uncertain inputs or also on any number of factors not modeled, such as individual detector characteristics and distance below the ceiling.

**6.** The design process often requires engineers to work beyond their areas of expertise: Problems can also occur when fire protection engineers are required to work in domains outside their expertise. Conservative assumptions

*The term *worst-case scenario* is used in this chapter to represent both worst-case **and** reasonable worst-case scenarios as understood in the fire protection design field.

made by well-intentioned engineers may not be as conservative as intended. For example, a design engineer intending to be conservative may assume that tenability would be violated if, out of a set of criteria, any one particular criterion, such as temperature or carbon monoxide, exceeded its minimum value. However, toxicity experts might argue that temperature and gas interactions cause tenability to be violated even when every individual species is in acceptable ranges. Likewise, a design engineer may assume that the time needed for a resident to react to an alarm be conservatively set equal to the travel time needed to go from one remote comer of the unit to the other most remote corner of the same unit. However, this may not be that conservative since even a fully ambulatory occupant may stop to gather belongings, rescue a pet, call a neighbor, and so forth.

**7. No** standardized methods exist to incorporate reliability **of** systems: The last barrier identified is the uncertainty surrounding both the reliability of a given fire protection device, system, or characteristic and the lack of a standardized method to incorporate reliability into performance-based engineering calculations and decisions based upon these calculations. We may be uncertain about the reliability of a given fire suppression system. Sometimes a fire suppression system is proposed as an alternative to passive fire protection, such as compartmentalization. However, these two alternatives have different reliabilities. There is uncertainty (e.g., no agreement) on how to account for these differences.

These seven barriers to determining and documenting achievement of agreed-upon levels of fire safety for a particular project must be addressed fully in order for all stakeholders to have a known level of confidence in the science-based predictions and the resulting final design. All seven barriers involve various types of uncertainty. Thus, there is a well-defined and important role for uncertainty analysis in fire safety engineering calculations. Although this clear role for uncertainty in improving the development and implementation of performance-based fire safety regulations exists, uncertainty analysis is clearly an uncomfortable topic for many of the stakeholders in the process.

### Difficulties with Uncertainty Analysis

Discussion of the proper treatment of uncertainty in a fire safety engineering calculation is difficult for several reasons:

1. *Magnitude of the problem.* It is widely assumed that a mixture of conservative assumptions and factors of safety can be used to explain away uncertainties. However, the magnitude of the problem is not clearly understood. Factors of safety that are applied at various stages of the analysis are not necessarily linearly related to the critical output parameters, potentially resulting in a reduced (or nonexistent) factor of safety in the results.
2. *Uncertainties that go unrecognized or ignored.* These types of uncertainties include those in variables hard-wired in scientific tools, those in tenability/performance criteria, those surrounding the selection of design fires, and those in human behaviors and values.
3. *Effect on the implementation of performance regulations.* It is feared that identification and treatment of uncertainty would show that our current ability to predict the buildup of heat and toxic products of combustion is not accurate enough to judge the acceptability of a proposed design with a high enough confidence level. This would delay implementation of the entire performance process until predictions of critical outcome criteria can be more certain.
4. *Quantitative methodology.* No quantitative methodology exists for treating uncertainty in performance-based designs. **A** methodology is needed that is both rigorous and user friendly.
5. *Impracticality.* It is feared that the mathematical rigor needed to conduct such an analysis would render the process impractical.
6. *Paucity of data.* To quantify uncertainty adequately, a large quantity of data would be needed to determine ranges of values for input parameters such as heats of combustion, rates of production of various gaseous species, and other important inputs. A large quantity of data would also be needed to validate predicted values with empirical data from real bum scenarios.

It should be pointed out that these are real and valid concerns due to the combination of poorly defined and unstructured problems, and the lack of a user-friendly methodology. Current common practice for conducting uncertainty analyses involves completing a series of single-variable sensitivity studies. Application of these techniques to a complete performance-based design containing hundreds of variables is impractical. The following sections focus on practical ways to identify and account for uncertainties in fire protection engineering design.

## Identifying Uncertainties in Fire Protection Engineering

When considering uncertainty in a fie protection engineering calculation, fire protection engineers typically consider first the uncertainties associated with the calculation inputs, usually empirically measured quantities such as heat-release rate. However, there are many other types of uncertainty integral to fire safety engineering design.

In a complete uncertainty analysis, not all uncertain parameters are treated quantitatively, only parameters or combinations of parameters with the potential to cause switchover in the final decision on the acceptability of a design. Others are negligible and best-guess values of these parameters can be used in the calculations. Still others, such **as** societal values, become policy or regulatory issues, not engineering issues. The intelligent use of safety factors can often cover more than one type of uncertainty. Still, it is useful to first identify sources and types of uncertainty from a broad perspective. Without first adequately identifying the sources of uncertainty, we cannot understand how best to handle them.

This section presents a taxonomy useful in developing a framework for understanding, identifying, and investigating uncertainties as a function of the steps in a fire safety engineering calculation. The taxonomy builds upon earlier published work.[4,10]

### Scientific Uncertainties

Scientific uncertainties are due both to lack of knowledge (e.g., in the underlying physics, chemistry, fluid mechanics, and/or heat transfer of the fire process) and to necessary approximations required for operational practicality of a model or calculation. Of the many types of uncertainty found in performance-based fire safety design calculations, scientific uncertainties are typically the most easily recognizable and quantifiable. The many types of scientific uncertainty can be roughly divided into five subcategories: **(1)** theory and model uncertainties, **(2)** data and input uncertainties, **(3)** calculation limitations, (4) level of detail of the model, and (5) representativeness of the design fire scenarios.

Theory and model uncertainties arise when physical processes are not modeled due to lack of knowledge of how to include them, processes are modeled based on empirically derived correlations, and/or simplifying assumptions are made. These types of uncertainties are present in most compartment fire models, where each of these factors lead to uncertainties in the results. Most compartment fire models are zone models, which make the simplifying assumption that each room can be divided into two volumes or layers, each of which is assumed to be internally uniform and that changes in energy or state are implemented immediately throughout the layers. Current zone models do not contain a combustion model to predict fire growth, forcing the model user to account for any interactions between the fire and the pyrolysis rate. Many compartment fire models also use an empirical correlation to determine the amount of mass moved between the layers.

Data and input uncertainties arise from both lack of knowledge of specific input values and variations in input values as a function of many factors, such as time, temperature, or region of the country. For example, the rate of heat release of a three-cushion upholstered sofa may be uncertain due to lack of available data for sofas with the same dimensions, stuffing, and cover materials. It may also be uncertain because the test method by which the heat-release rate was measured could not specify all combinations of ignition source and strength, and because there are inaccuracies inherent in the instrumentation used in the test. Other inputs such as concentrations of toxic gases produced vary with time as the fire develops and are uncertain. The species production rates used to predict concentrations are a function of the material or combination of materials actually burned. This is unknown a priori at the design stage.

For most fire models and calculation procedures, very different answers can result depending on the calculation limitations, control volume selected for modeling, the level of detail of the model, and the model-domain parameters specified. Model-domain parameters set the scope of the system being modeled and define the model's level of detail and/or baseline properties. Though these parameters or quantities are often ignored during uncertainty analysis, they have the potential for considerable impact.[1] This has been shown for fires in high bay spaces. Differences in the outcome criteria such as maximum temperature, and time to activation of fire detectors and sprinklers are found when a large space is modeled with a simple zone fire model versus a more detailed computational fluid dynamics model.[17] Differences in the outcome criteria are also found when a large space, which is typically subdivided by draft curtains,* is modeled. If a control volume is drawn around a single draft-curtained area (as opposed to drawing the control volume around multiple draft-curtained areas or around the entire building), higher temperatures and faster activation times of installed fire protection devices will be predicted. Also, significant to the uncertainty in the outcome parameters are the index variables of the model. Index variables are used to identify a location in the domain of a model or to make calculations specific to a population, geographic region, and so forth.

Uncertainty arises in both the number and type of design fire scenarios that need to be modeled for a given design/building. There may be significant differences between reality and the design fire scenarios that were used to judge the adequacy of the performance-based design. Variations in the ignition source, rate of growth, and/or the materials burned affect confidence in the results. It is unclear whether all statistically significant fire scenarios must be modeled or whether worst-case or reasonable worst-case scenarios are adequate. Furthermore, a worst-case scenario may be defined in terms of many different variables. A scenario may be worst-case because it is most likely to cause death, because it has potential for large property loss, or for other reasons.

### Uncertainties and Variability in Behavior

Human behavioral uncertainties concern both the way in which people act in a fire and how these actions should be considered during steps in the design process (e.g., definition of project goals, selection of performance criteria, and development and evaluation of trial designs). Behavioral scientists tell us that human actions can range from somewhat predictable to unpredictable. Actions are more predictable when choices are limited, procedures are practiced, the situation is not novel, and little chaos is present. Unfortunately, during a typical fire, few if any of these conditions occur. Brannigan discusses what he calls *intentional uncertainty* in relationship to human behavior.[16] Brannigan states, "human decision making does not follow the same kind of well understood rules that control the physical science variables used in models. Human decisions represent intentional uncertainty."

Human behavior in response to a fire alarm must be modeled in terms of time to respond to the alarm and type of response. Does the person immediately begin evacuating the building? Does he/she take the stairs or

*A draft curtain is a barrier that extends a certain vertical distance down from the roof or ceiling. Draft curtains are installed to subdivide a large area with the intent of corralling the heat and smoke.

the elevator? What factors into that choice? Does the person try to fight the fire? Does the person stop to gather personal possessions or call a neighbor? Another area of human behavior relevant to performance-based calculations is behavior during egress. Do people use the best exit or the most familiar one? How long do people take to start to exit?

Human factors also affect the analysis needed for identifying goals and objectives and developing performance criteria. Fire safety goals typically include levels of protection for people, with performance criteria being a further refinement of these objectives. Performance criteria are numerical values to which the expected performance of trial designs can be compared. What range of occupant characteristics, such as age or disability, should be considered? How do human behaviors, for example, during egress, influence the numerical values chosen for performance criteria?

When developing and evaluating trial designs, the efficacy of the proposed fire safety measures mitigating all likely fire scenarios should be determined. This involves varying human behavioral elements. For instance, two very different fire scenarios could develop from the same cooking-initiated design fire: (1) a grease fire from cooking sets off a smoke detector that alerts the occupant who reacts and properly extinguishes the fire while it is still small; or (2) the occupant forgets and leaves a pot simmering on a burner, takes a sleeping aid, and goes to bed. The overheated pot ignites and the fire spreads to one or more adjacent items. The First International Symposium on Human Behaviour in Fire was held in 1998. Proceedings from this conference provide information useful in addressing these issues.[18]

### Uncertainties and Variability in Risk Perceptions and Values

There is both variability and uncertainty in the way people perceive and value risk. Capturing differences that people have in their perceptions of risk and values related to risk is a necessary step in the design process. Research has shown that although people typically view consequences from voluntary risks less severely than equal consequences resulting from an unknown and/or involuntary risk, there is variability.[19] For example, while some people would agree that an increase in risk to fire fighters (people who accept risk as part of their job) is justifiable if a corresponding decrease in risk to the public could be achieved, others would not. Few studies have been conducted that clearly demonstrate how society values fire safety risks at the level needed to support performance-based trade-offs. Some work on incorporating risk concepts and identifying levels of acceptable risk is discussed in Section 5, Chapter 12 of this handbook, “Building Fire Risk Analysis.” It is important to identify where value judgments enter into a performance-based calculation and to make any assumptions explicit regarding values and the impact of different values on the final design.

Another important factor is the concept of *equivalency.* Equivalency can mean different things to different stakeholders. For example, one person may determine that noncombustible construction is equivalent to an installed sprinkler system if they are both shown to provide time to fully egress the building. Another may argue that they are not equivalent—that the reliability of the sprinkler system is less. Designs may be equivalent in terms of life safety, property protection, business interruption, injuries, and/or prevention of structural collapse, but they are most likely not equivalent in all regards. It is, therefore, important to make explicit the assumptions that equivalency depends on.

### Uncertainties Related to the Life-Cycle Use and Safety of Buildings

Many factors change over the lifetime of a building. The uncertainties surrounding future use, occupancy, and other factors contribute to the difficulty in conducting a structured, performance-based design. Even daily fluctuations in these design parameters can affect the safety of a building. For example, a building or area of a building that is normally occupied 24 hours per day may become unoccupied (or occupied by very different people) for extended periods of time due to extraneous factors (e.g., business closing, maintenance, renovation). The characteristics of the different occupants can lead to very different design considerations. Other changes that may affect the life-cycle safety of the building are fire service characteristics such as location, expected response time, and operating procedures and capabilities.

### Uncertainties Related to Providing for Equity and Incorporation of Societal Values

Providing for equity and incorporating societal Values involves determining what is important to the stakeholders and to what degree protection should be provided. A mechanism should be provided to ensure equal outcomes for subgroups. Since most projects have many stakeholders, such as building owner, design engineer, architect, code official, and the public (users of the building), it is difficult to assign worth to the usefulness or importance of something and apply it across all individual and societal issues. The key here is that decisions that change when a value, attitude, or risk perception varies must be made explicit in the design. Agreement on these key decisions by all stakeholders is critical to the success of a performance-based design.

### Relation to Steps in the Design Process

Several types of uncertainty will be encountered at each step in a performance-based design process or during the process of setting a new prescriptive requirement. For example, when developing performance criteria, one will have to deal with scientific uncertainty, such as determining what level of carbon monoxide will cause unacceptable consequences, and how to account scientifically for interactions between products of combustion. One will also have to deal with issues of equity and societal values. At present, performance criteria are not established nor agreed upon. Changes to the set of performance criteria selected could cause the same design for the same building to be deemed acceptable in one jurisdiction and deemed unacceptable in another jurisdiction. Uncertainties related to life-cycle use and safety of buildings also arise when selecting performance criteria. Over the life cycle of the building, many factors, such as use and occupant characteristics, change.

### Nature and Sources of Uncertainty

In conclusion, uncertainty is a broad and general term used to describe a variety of concepts including, but not limited to, lack of knowledge, variability, randomness, indeterminacy, judgment, approximation, linguistic imprecision, error, and significance. Many of these uncertainties are inherent in the design process itself. Variations in analysis parameters, assumptions, or model inputs, may cause output criteria to change. Switchover occurs when outcome criteria change enough so as to cause a change in the design decision (e.g., the acceptability of a final design). It is critical to know whether different sets of reasonable inputs, scenarios, or parameters used in a fire safety engineering design have potential to cause switchover and to lead to different acceptable designs. This section provided an overview of terminology used to describe uncertainty; described aspects of the design process that introduce uncertainty; and presented a taxonomy useful as an aid in identifying uncertainties.

## Treatment of Uncertainty

### Treatment of Uncertainty with Safety Factors

Safety factor and margin of safety are two commonly used terms in the field of engineering. The dictionary defines factor of safety *in* terms of stress: "The ratio of the maximum stress that a structural part or other piece of material can withstand to the maximum stress estimated for it in the use for which it is designed." Safety factors do not just apply to stress, however. The idea of a safety factor is that the design values are multiplied by the factor of safety and the design is checked to ensure that the design is safe at the larger value (i.e., the product of the design value and the safety factor). Safety margins are a slightly different concept. A safety margin is additive and not multiplicative. A safety margin is defined as the difference between the design value and the value that would no longer be safe.

### Implied versus Explicit Safety Factors

Safety factors are used with both prescriptive and performance codes. These factors of safety can be implied or explicit. Implied safety factors generally are found at various substages or components of a design. Implied safety factors provide for an extra margin of safety simply attributable to the choice of a component of a system. Implied safety factors may also take the form of conservative assumptions or worst-case scenarios. Explicit safety factors are multipliers applied to critical analysis parameters, often (and preferably) the final outcome criteria used to judge the acceptability of a design. Both types of safety factors are used to increase safety by lowering the probability that critical values of analysis parameters will be reached or exceeded.

### Use of Safety Factors in Prescriptive and Performance Codes

An example of an implied safety factor in a prescriptive code is use of a pipe material or thickness that exceeds the strength and durability needed to meet the requirements of a sprinkler system. Pipe schedules have implied safety factors. An example of an explicit safety factor incorporated into a prescriptive code provision is a requirement to use a sprinkler flow density 1.5 or some other multiple higher than the minimum shown experimentally to control a given type of fire. In this example, the safety factor is used to cover for uncertainties in the measurement of the needed flow density, variations in the actual fuel package versus the fuel package tested, and uncertainties and variations in geometry, building characteristics, and so forth. An example of an implied safety factor in a performance code is an assumption that the rate of production of carbon monoxide for a given fuel package is equal to the rate of production of the component fuel with the highest production. An example of an explicit factor of safety incorporated into a performance-based design is to directly multiply the time necessary for egress by a factor of *2.*

### Selecting an Appropriate Factor of Safety

The first step in the use of safety factors is to determine which analysis parameters would be appropriate for the application of a safety factor. When a factor of safety is applied to measures of the final outcome criteria, it is most clear what margin of safety has actually been achieved; however, it is least clear how to alter the design specifications when a higher factor of safety is desired.

Safety factors may also be applied to different analysis parameters at various stages of the analysis. Careful judgment must be used, however, when applying these intermediate safety factors, because the quantity to which they are applied may not be linearly related to the final outcome criteria. Even if the quantity is linearly related to the final outcome criteria, it may not possess a 1 : 1 relationship. Specifically, a 1: 1 relationship exists when a unit change in the analysis parameter causes a proportional unit change in the outcome criteria. In fire protection engineering calculations, input variables and analysis parameters are not often linearly related to outcome criteria such as upper-layer temperature. Also, they usually do not share common units **of** measure. In fire protection engineering calculations, time is the only common measure. It is likely that a safety factor of 2 applied to an intermediate quantity will not allow for a safety factor of 2 in the final design. In some cases, a safety factor of **2** applied to an intermediate quantity may not allow for any factor of safety design.

This is particularly true for implied factors of safety often found in the form of conservative assumptions. For example, an assumption that a fast growth rate fire is a worst-case scenario is not true in all cases. A fast-flaming fire may not pose the greatest danger if it activates the sprinkler more quickly. A slower developing fire may be more able to overpower the sprinkler in some circumstances, and a fire originating in an unprotected or shielded space, even though slower growing, may also be more deadly. Therefore, if we wish to provide a safety factor of **2** to the time available to safely egress a building, we cannot assume that doubling the fire size (heat release rate) will achieve this goal. Heat release rate is not linearly related to time to critical temperature.

When an explicit factor of safety is applied, one may chose a value of 1.5, **2,** or even higher. How much of a margin of safety is appropriate is as much a function of how much confidence we have in the predictive equations (i.e., are we using a factor of safety as a factor of uncertainty?) used in the calculations as it is of the stakeholders' risk tolerance. It should be noted, however, that increasing the margin of safety usually corresponds to an increase in cost of the project. When historical performance data is available, it can be used to set factors of safety. Otherwise, safety factors are usually set by expert judgment or mandated in policy. Safety factors are set to reflect confidence in the design equations as well as to reflect the stakeholders' acceptable risk tolerance. New specialized methods are being developed for deriving appropriate factors of safety.

### Combining Safety Factors

First, it must be stated that there are no official rules, that is, none published and agreed upon by the fire safety community at large, for combining safety factors. The following list of suggestions and potential pitfalls was compiled by the author. After a fairly thorough review of the literature, specific numbers and justifications for safety factors were found lacking. To get good quantitative numbers for safety factors, historical data are needed.

Track the effect of each factor of safety: The effect of each factor of safety on the outcome criteria can be determined by changing the value of the safety factor and observing the net change in the outcome criteria relative to the net change in the safety factor. When the equations are not overly complicated, it may be possible to derive this relationship directly using partial derivatives. For conservative assumptions, the effect of the assumption should be tested by repeat calculations.

Watch for variance: If the normal variation in the population is sufficiently large, a factor of safety applied to the mean will not cover all or even most of the people who will be in the building. For example, if the baseline walking speed is estimated as the walking speed of a young, healthy individual and a safety factor of 2 is used, that would not cover the walking speed of an elderly person or person with physical disabilities if their speed was less than half the average.

**Don't** assume safety factors are additive: Factors of safety applied to two individual parameters in the analysis will not necessarily provide a total factor of safety equal to the sum of each individual safety factor. The total safety factor could be more or less than the sum of the two individual safety factors. As was discussed earlier, analysis parameters are often not linearly related to outcome criteria. They are most likely in different units of measure, and analysis parameters are likely not linearly related to each other. For these reasons, safety factors cannot be assumed to be additive.

Account for both positive and negative effects on safety: ***An*** explicit factor of safety or design assumption may have either a positive or negative contribution towards safety. Careful thought, engineering judgment, and testing using the calculation procedure must be used to test for the effects of each factor of safety and/or design assumption made. For example, doubling the heat of combustion may be conservative in predicting upper-layer temperature whereas doubling the radiative fraction will have the opposite effect.

Evaluate for multiple performance criteria: Also, since most fire safety engineering designs are judged on multiple performance criteria, what might constitute an implied factor of safety for one outcome criterion might constitute a reduction in safety for another parameter. For example, if a soot yield value is conservative for smoke detector activation, then it could not simultaneously be conservative for life safety.[20]

Realize effects may change with time: The relative importance of individual input variables, and thus the factors of safety applied to them, may be a function of time. In particular, variables may be limiting factors in the analysis during the time period of preflashover, and in the postflashover time period have little or no effect. Since in fire protection engineering we often deal with two distinct phases of the fire represented by different physics and mathematics, we must be careful to be aware of changes in the effects of a parameter in these very different phases of fire development.

### Derivation of Safety Factors

Researchers at the University of Lund[21,22] have been conducting research on the application of the FOSM (first-order second-moment) methodology for fire safety engineering design. They have applied the FOSM method to derive safety factors for use in fire safety engineering design calculations. The safety index is represented by $\beta$, the distance from the origin to a failure line (limit state). $\beta$ is also referred to as a reliability index where reliability is defined as the probabilistic measure of assurance of performance. $\beta$ can also be thought of as the overall safety factor for the design.

The overall concept for conducting a design is to specify input data, choose a target reliability index $\beta$ (they suggest 1.4, which is approximately equivalent to a probability of failure of 8 percent on condition that a fire has started), and vary the design parameters to be determined until the chosen value of @ has been obtained. In this type of analysis, design parameters include design door width and time to detection.[21]

They have also applied the FOSM methodology to derive the safety factor, β, for a design. In this case, design parameters such as door widths and time to detection are already known. *An* example is worked out for a shopping center.[22] There are some admitted shortcomings to applying this methodology to an actual design problem. First, the importance of the uncertainties in the input parameters needs to be investigated via a sensitivity analysis. A method of incorporating this uncertainty would then need to be standardized.

## Techniques for the Quantitative Treatment of Uncertainty

It is important not only to recognize the various types of uncertainty, but also the different types of quantities for which the uncertainty exists, since they need to be treated in different ways. There is a standard procedure for quantifying uncertainty in empirical quantities. This procedure, sometimes referred to as classical uncertainty analysis, is based on the mathematics of probability and statistics. However, as shown by the taxonomy, in any fire safety engineering calculation or decision, there are many nonempirical parameters and assumptions used in the calculations. It is not always appropriate, meaningful, or even possible to treat the uncertainty in these nonempirical parameters by these same probabilistic methods. It has been argued that "probability is an appropriate way to express some of these kinds of uncertainty but not others."' The next sections present quantitative methods appropriate for the expression of uncertainty in various types of quantities.

### Techniques for Quantifying Measurement Uncertainty

Many calculation and model inputs are empirical in nature. To be empirical, variables must be measurable and have a true value. Empirical quantities in the domain of fire protection engineering include the heat-release rate, the burning rate, and the radiative fraction of a given fuel. Classical uncertainty analysis refers to a statistical method of determining the random and systematic errors (and from them the total error) for a set of measurements. Random error and statistical variation results because no measurement of an empirical quantity can be absolutely exact. Imperfections in the measuring instruments and observational technique will inevitably give rise to variations from one observation to the next. The resulting uncertainty depends on the size of the variations between observations and the number of observations taken.

Classical statistical techniques such as standard deviation, confidence intervals, and others can be used to quantify this uncertainty. These statistical techniques are presented in Section 1, Chapters 11 and 12 on probability and statistics, respectively. **A** full discussion on uncertainty in measurement is found in the U.S./ISO guide2 and in the NIST guide.[23] The NIST guide describes two types of evaluations of uncertainty. A Type A evaluation of standard uncertainty may be based on any valid statistical method for treating data. Three examples are **(1)** calculating the standard deviation of the mean of a series of independent observations; **(2)** using the method of least squares to fit a curve to data in order to estimate the parameters of the curve and their standard deviations; and **(3)** carrying out an analysis of variance (ANOVA) in order to identify and quantify random effects in certain kinds of measurements.

A Type B evaluation of standard uncertainty is usually based on scientific judgment using all the relevant information available, which may include previous measurement data, experience, manufacturer's specifications, and calibration reports. There is not always a simple correspondence between the classification of uncertainty components into categories A and B and the commonly used classification of uncertainty components as random and systematic.

The nature of an uncertainty component is conditioned by the use made of the corresponding quantity, that is, on how that quantity appears in the mathematical model that describes the measurement process. When the corresponding quantity is used in a different way, a random component may become a systematic component and vice versa. The NIST guide also differentiates between uncertainty and error. It is assumed that a correction is applied to compensate for each recognized systematic effect that significantly influences the measurement result. The relevant uncertainty to associate with each recognized systematic effect is then the uncertainty of the applied correction.

### Techniques **for** Assessing Uncertainty in Analysis Parameters, Assumptions, and Value Parameters

Probabilistic techniques used to quantify measurement uncertainties are not applicable to uncertainties in establishing performance criteria or uncertainties regarding values such as the value of life. These uncertainties should be evaluated with techniques that make explicit the effect of the uncertainty on the value of all decision variables. Decision variables in fire protection engineering are such things as level of acceptable fire safety and installation of fire protection devices. If a quantity is a decision variable, then by definition it has no absolute, true value. It is up to the decision maker who exercises direct control to decide its value. Morgan and Henrion state that, "*The question of whether a specific quantity is a decision variable, **an** empirical quantity, or some other type of quantity depends on the contexf and intent of the model, and particularly **who** the decision maker is*" (emphasis added).' For example, in performance-based design, the minimum, permissible escape time during a fire may be a decision variable for the regulatory body, but it may be an empirical quantity from the viewpoint of the fire protection engineer.

Value parameters represent preferences of individuals. One controversial value parameter is the value of premature death avoided, often referred to as the value of life. Another is risk tolerance or risk preference, a parameter used to specify a degree of risk aversion when comparing uncertain outcomes. The effect on the outcome of an analysis caused by differences in value parameters should be demonstrated explicitly. This is done by repeating the analysis for a range of possible inputs of the value parameter(s) to determine if a change in the outcome occurs that someone would care about. Several techniques that aid in the evaluation of uncertainty in these types of quantities are presented below. For all these techniques, the effect of various values of analysis parameters, assumptions, and value parameters is made explicit.

**Bounding:** Evaluating the extremes of the range of possible values of an uncertain quantity. If the extreme values at both ends are acceptable, a more complex and costly analytical uncertainty analysis may be avoided. For example, suppose we bound the ambient room temperature between a low and a high value. If we are trying to predict carbon monoxide buildup in a room, we may find that the results are either not sensitive to ambient temperature, or the range of predicted values of carbon monoxide, based on the range of ambient temperatures, is completely acceptable. We may either eliminate ambient temperature as a variable or set it to our best-guess estimate. We do not need to quantify the uncertainty in the ambient temperature any further.

**Sensitivity/sensitivity analysis:** Sensitivity of a design to modest variability and uncertainty must be explicitly understood. Sensitivity analysis is useful in assessing the consequences of uncertainty in data and in assumptions. By testing the responsiveness of calculation results to variations in values assigned to different parameters, sensitivity analysis allows the identification of those parameters that are most important to the outcome criteria. It does not tell the decision maker the value that should be used, but it can show the impact of using different values.

**Parametric analysis:** A parametric analysis is a particular type of sensitivity analysis. In parametric analysis, detailed information is obtained about the effect of a particular input on the value of the outcome criterion. This is done by evaluating and plotting the outcome criterion for a sequence of different values for each input, holding the others constant.

**Importance/importance analysis:** An importance analysis is a particular type of sensitivity analysis that determines which of the uncertain input variables contributes most to the uncertainty in the outcome variable. The results are used to focus on getting more precise estimates or building a more detailed model for the one or two, or small group of, most important inputs. Importance here is defined as the rank-order correlation between the output value and each uncertain input. Each variable's importance is calculated on a relative scale from 0 to 1. An importance value of 0 indicates that the uncertain input variable has no effect on the uncertainty in the output.

**Comparative analysis:** Comparative analysis is a technique used to evaluate risks, and the costs to mitigate them, by means of comparison to other similar risks. This technique is useful in evaluating perceptions of risk tolerance. Researchers[24] conducted a comparative analysis of the cost of mandating residential fire sprinklers with the cost of mandating other methods of reducing residential deaths such as radon remediation and ground fault interrupters.

**Expert elicitation:** Where hard data does not exist and is not possible to create experimentally, an expert elicitation is often conducted in order to obtain expert judgment of an uncertain quantity. An excellent discussion of the techniques for conducting an expert elicitation is provided in Chapter 6 of *Uncertainty*.[1]

**Switchover:** Variations in analysis parameters, assumptions, or model inputs, will cause output criteria to change. Switchover occurs when outcome criteria change enough so as to cause a change in the design decision (e.g., the acceptability of a final design).

## Techniques for Assessing Uncertainty and Sensitivity in Complex Models

Several of the scientific uncertainties discussed in the taxonomy presented above can only be evaluated by examining the structure of the fire model. These include theory and model uncertainties, calculation limitations, and level of detail of the model. Uncertainties arise when physical processes are modeled based on empirically derived correlations, and/or simplifying assumptions are made. Other physical processes are not modeled due to lack of knowledge of how to include them. As stated earlier, most compartment fire models are zone models, which make the simplifying assumption that each room can be divided into two volumes or layers, each of which is assumed to be internally uniform. Current fire models do not contain a combustion model to predict fire growth, and many compartment fire models use an empirical correlation to determine the amount of mass moving between the layers.[25] There are uncertainties introduced by these modeling approximations.

**Fire model validation:** Fire model validation has become a much-discussed topic since fire models have become relied upon as a means of verifying that a fire safety engineering design meets a set of performance objectives. Work is being done to characterize the additional output uncertainty due to modeling approximations. Part of this work is focused on aiding the user in selecting a model, or set of models, appropriate to the type of prediction(s) needed. Some researchers have suggested a Bayesian framework where each available model is treated as a source of information that can be used in a prediction.[26,27]

In addition, work is ongoing to evaluate computer fire models by comparison of model predictions to predictions of other models or with experimental data. These comparisons are helpful to the user in determining the level of uncertainty likely from a model prediction for a similar set of conditions. However, these comparisons are difficult since they involve comparing two time-series curves, the experimental measurements, and the predicted values. Historically these comparisons have been largely qualitative. The use of a branch of mathematics called functional analysis to make comparisons of these time-series curves is being investigated. This allows lengths, angles, and distances between two arbitrary curves to be defined and quantified.[28] Further validation issues that must be addressed were discussed among various groups of fire safety professionals at the Conference on Fire Safety Design in the Twenty-First Century.[29] Jones discusses issues that must be addressed in a report entitled, "Progress Report on Fire Model Validation."[30] Once a model is selected, it is useful to know the sensitivity of that model's output predictions to the values selected for the inputs.

Sensitivity **of** output predictions to input values: When selecting and using a fire model, it is important to know the sensitivity of the predicted outcome criteria to the model inputs. In order to facilitate this, several quantitative methods for determining the sensitivity of model predictions to model inputs are described below along with a brief discussion of their positive and negative attributes and limitations of application. These are also discussed in ASTM **1355-92,** Standard Guide for Evaluating Predictive Capability of Computer *Fire Models.*[31]

**A differential/direct method:** For a system of time-dependent, ordinary differential equations, it is possible to solve directly for the partial derivitive of the predicted values with respect to each of the input variables. This set of partial derivatives measures the sensitivity of the solution with respect to changes in the input parameters:

$$Y_I = f_I = (c_1, c_2, \ldots, y_1, y_2, \ldots, t)$$

where $c_k$ are rate parameters.

We simultaneously solve for both $y_I$ and a set of sensitivity functions, $\delta y_i/\delta c_k$, over all times $t$. These partial derivatives measure the sensitivity of the solution with respect to uncertainties in the parameters $c_k$ and in initial conditions. Often these parameters are not accurately known. Dickson provides an example of a direct solution of a set of ordinary differential equations that composes a large computational model of atmospheric chemical kinetics.[32]

Response surface replacement: Multiple runs, $n$, of the computer model are made. The model output $Y_i$ and inputs $X_{1i}, \ldots, X_{ki}$, I = 1,..., $n$, are used to estimate the parameters of a general linear model of the form:

$$Y = \beta_0 + \sum_j \beta_j X_j$$

The estimated model is known as a fitted response surface, and this response surface is used as a replacement for the computer model. All inferences with respect to uncertainty analysis and sensitivity analysis for the computer model are then derived from this fitted model.[33] Construction of a response surface without specification of the probability distributions for all input variables is discussed by Iman.[34] It is suggested, in fact, that when using certain sampling techniques to build a response surface, it may be desirable to ignore probability distributions and use only the ranges of the variables. Iman provides a good discussion of using a response surface method to conduct a sensitivity analysis and provide a ranking of input variables in a second paper.[35] Beller has discussed the use of response surfaces for modeling upper-layer temperature and layer height.[36]

Monte Carlo sampling: In uncertainty analysis employing Monte Carlo sampling; it is desired to estimate the distribution function and the variance for the particular output variables under consideration. The uncertainty surrounding each input is represented mathematically and often probabilistically by its individual distribution. When all probability distributions for all uncertain quantities are put together, a simulation model is built that is believed to capture the relevant aspects of the uncertainty in the problem. After running the simulation many times, an approximation of the probability distribution of the output variables is generated. The more simulations that are carried out, the more accurate the approximation becomes.

### Advantages and Disadvantages **of** Each Technique

Iman and Helton state in their paper, "Investigation of Uncertainty and Sensitivity Analysis Techniques for Computer Models," some of the characteristics of large and complex computer models.[33]

- There are many input and output variables.
- The model is time consuming to run on the computer.
- Alterations to the model are difficult and time consuming.
- It is difficult to reduce the model to a single system of equations.
- Discontinuities exist in the behavior of the model.
- Correlations exist among the input variables, and the associated marginal probability distributions are often nonnormal.
- Model predictions are nonlinear, multivariate, time-dependent functions of the input variables.
- The relative importance of the individual input variables is a function of time.

Fire models often posses many and sometimes all of these characteristics. Iman and Helton evaluated the above three techniques as applied to large, complex models having many of the above characteristics. Their evaluation included ease of implementation, flexibility, estimate of the cumulative distribution function (CDF) of the output, and adaptability to different methods of sensitivity (analysis). Their findings clearly show that the technique that had the best overall performance was Monte Carlo sampling. They found that a differential analysis provides good local information about the inputs but does not extend well to a global interpretation. Also, a very real problem with

*There are many sampling techniques. Monte Carlo is one, well-accepted sampling method that has certain statistical advantages but may not be the best choice *in* all cases.

differential analysis lies in the difficulty of implementation. Response surface replacements were not recommended because the underlying models are often too complex to be adequately represented by a simple function.

The following section describes a methodology for application of uncertainty analysis to fire safety engineering calculations. This methodology employs Monte Carlo sampling. It also incorporates many of the techniques described in previous sections for quantifying measurement uncertainty, and assessing uncertainty in analysis parameters, assumptions, and value parameters.

## Application of Uncertainty Analysis to Fire Safety Engineering Calculations

The fire safety community needs to begin to move forward from discussing a set of issues and concerns relating to uncertainty in fire protection engineering to agreeing as a community on practical steps to execute an uncertainty analysis. This section demonstrates a suggested methodology that quantitatively treats variability and uncertainty and applies it to a complex fire protection engineering problem. The methodology suggested is a generic methodology that is applicable to a wide range of fire protection engineering calculations and fire safety design issues. For example, application of the methodology is appropriate for engineering calculations such as those that predict upper-layer temperatures and concentrations of products of combustion. The methodology may also be applied to calculations of time needed to egress. It ties together the issues discussed above regarding uncertainties in the design process and the problem of switchover. Here, a brief introduction to and overview of the methodology is presented. A full description of the methodology and a worked case study of an actual building can be found in Notarianni.[37]

### Overview of the Performance-Based Design Process with Uncertainty

The methodology is rigorous but comprehensible. It breaks up the process of conducting an engineering design calculation with uncertainty analysis into identifiable steps, each of which can be expanded or contracted to fit specific design problems. Table 5-4.1 shows the steps in conducting a performance-based fire protection engineering design. The column labeled Performance-Based Design Process lists the steps in the performance-based design process as detailed in the SFPE guide.[11] The right column lists the steps in the performance-based process with uncertainty. Steps or parts of steps in bold signify suggested modifications to the current design process. Steps **1–3** are modified by incorporating treatment of uncertainties noted in parentheses and detailed in the taxonomy presented earlier. The intent of each step does not change; however, the process is made explicit and standardized.

The quantitative methodology for the application of uncertainty analysis is applied throughout Steps 4–8. In Step 4 a probabilistic statement of performance is developed. In Steps 5–7, candidate designs are developed and a process for evaluating these designs through simulation with uncertainty analysis is described. Step **8** now includes a decision of acceptability that makes use of the results of the quantitative uncertainty analysis. Steps **9** and **10** remain the same. It should be noted that performance-based designs may require an iterative process. If in Step 8 the candidate designs are deemed unacceptable, the process returns to Step **6** to develop new candidate designs. If no acceptable design is found to meet the goals and objectives, Steps **1–3** must be revisited.

### Steps 1–3: Define Scope, Goals, and Objectives

Many of the types of uncertainties discussed in the taxonomy are important to consider during the process of setting the scope, goals, and objectives of a project. These three steps are described below; for each step, one example of a type of uncertainty to consider is provided.

The first step in the performance-based design process is to define the scope of the project. The project scope is an identification of the boundaries of the performance-based analysis or design. The SFPE guide suggests consideration of several aspects of scope such as occupant and building characteristics and intended use of the building. In the first section of this chapter, indeterminacy was discussed as well as uncertainties related to the life-cycle use and safety of buildings. Indeterminacy affects the scope in that it is impossible to know what the occupancy and furnishings will be in a building at some point in the future. Therefore when assumptions are made regarding occupant and building characteristics, some investigation of the sensitivity of the final design to changes in occupant and building characteristics should be made and documented. If switchover occurs for a particular value of one or a combination of analysis parameters, assumptions, or values, this needs to be made explicit.

The second step in the design process is identifying and documenting fire safety goals of various stakeholders. These include levels of protection for people and property and provide for continuity of operations, historical preservation, and environmental protection. For example, when identifying goals of various stakeholders, a mechanism needs to be provided to ensure equal outcomes for subgroups, including the building owner, design engineer, architect, code official, and the public (end users). Because it is difficult to assign worth in the usefulness or importance of something and apply it across all individual and societal issues, the key here is that decisions that change when a value, attitude, or risk perception varies must be made explicit in the design documentation.

The third step in the design process is the development of objectives, which are essentially the design goals that have been further refined into values quantifiable in engineering terms. Objectives might include mitigating the consequences of a fire expressed in terms of dollar values; loss of life; or maximum, allowable conditions such as the extent of fire spread, temperature, or spread of combustion products. Uncertainties arise here in risk perceptions and values. There is both uncertainty and variability in the way people perceive and value risk.

Capturing differences people have in their perceptions and values related to risk is a necessary step in the design process. For example, it may be a goal of the stake-

**Table 5-4.1** *Steps in the Performance-Based Design Process with and without Uncertainty*

| | Performance-Based Design Process[11] | | Performance-Based Design Process with Uncertainty[37] |
|---|---|---|---|
| Step 1 | Define project scope | | Define project scope (uncertainties related to life-cycle use and safety of buildings) |
| Step 2 | Identify goals | | Identify goals (uncertainties related to equity and incorporation of societal values) |
| Step 3 | Define stakeholder and design objectives | | Define stakeholder and design objectives (uncertainties related to risk perception and values) |
| Step 4 | Develop performance criteria | | Develop probabilistic statement of performance (criteria, threshold, probability, time) |
| Step 5 | Develop design fire scenarios | | Develop a distribution of design fire scenarios |
| | | (a) | Select calculation procedure(s) |
| | | (b) | Identify uncertain input parameters |
| | | (c) | Generate a distribution of design fire curves |
| | | (d) | Define distributions of and model correlations among other input parameters |
| | | (e) | Select sampling method and determine number of scenarios |
| Step 6 | Develop candidate designs | | Develop candidate designs |
| Step 7 | Evaluate candidate designs | | Evaluate candidate designs |
| | | (a) | Calculate a set of values for each outcome criteria and create cumulative distribution functions |
| | | (b) | Determine sensitivity to elements of probabilistic statement of performance |
| | | (c) | Evaluate base case (optional) |
| | | (d) | Determine effect of each candidate design on each of the scenarios |
| | | (e) | Evaluate uncertainty importance |
| Step 8 | Design meets performance criteria? | | Design meets all four elements of probabilistic statement of performance? |
| Step 9 | Select final design | | Select final design |
| Step 10 | Prepare design documentation | | Prepare design documentation |

holders to protect historical features of the building or to protect against business interruption or loss of operating capability. Stakeholders with different values may see these needs differently. It is important to identify where value judgments enter into a performance-based calculation and to make any assumptions explicit regarding values and the impact of different values on the final design.

The following discussion is focused on incorporating uncertainty directly into Steps 4–8. Here, we develop a probabilistic design statement, develop a distribution of statistically significant fire scenarios, calculate a set of values for critical outcome criteria, and evaluate each candidate design to determine whether the design meets the performance criteria within acceptable uncertainty bounds.

### Step 4: Develop Probabilistic Statement of Performance

The fourth step in the design process is the development of probabilistic statement(s) of performance, that is, criteria by which to judge the acceptability of the design. These criteria are a further refinement of the design objectives and contain numerical values to which the expected performance of the candidate designs can be compared. Each probabilistic design statement contains a minimum of four elements: probability, time, performance criteria, and threshold value. For example, an objective may be to maintain tenable gas concentrations in the corridor. A corresponding probabilistic design statement for life safety might specify that the design must allow for a 0.9

probability of having 4 min or more before a temperature of 65°C is reached in the corridor. Thus all four elements are included: probability, time, performance criteria, and threshold value. A location is also specified.

There are many issues to be addressed when establishing probabilistic statements of performance. For example, which criterion should one evaluate? One could select, instead of or in addition to temperature, levels of carbon monoxide, heat **flux,** or obscuration. There is disagreement in the literature as to what values of each of these cause negative consequences. The negative consequences must be defined; that is, should the threshold values represent incapacitation or lethality? Also, the probability element involves determining the level of acceptable risk to the stakeholders, and establishing criteria for time to untenability involves understanding behavioral patterns of people in fire as well as making value judgments as to which subpopulations one is trying to protect. The sensitivity of the design to each element of the probabilistic statement of performance is evaluated in Step 7b.

Based on this type of sensitivity analysis, a two-tiered probablistic statement of performance may be developed based on any of the four elements as well as location. For example, the probabilistic statement of performance may say that the design must allow for a 0.9 probability of having 4 min or more before untenability based on a temperature of 65°C is reached *and* a 0.9 probability of having 6 min or more before 100°C is reached. The design statement may be specified in other ways:

- Include two probability levels, such as the design must have greater than or equal to a 0.95 probability of *X and* less than or equal to a 0.1 or more probability of *Y.*
- Provide a variation such as the design must provide for a 0.9 probability of providing **4** min before 65°C is reached and a 0.9 probability of having 8 min or more before untenable gas conditions are reached.

These are just a few of the possible specification options. **Also,** the location of evaluation matters. Untenability can be evaluated as a minimum anywhere in any room, including the room of origin, or it can be evaluated along the egress path. These two analyses may give different results in terms of acceptability.

### Step 5: Develop a Distribution of Design Fire Scenarios

One of the most important pieces of the methodology is how to generate a set of realistic input scenarios. It is important that this set include a combination of scenarios that represent statistically both the types of fires and the frequency at which they occur in a given occupancy. The input scenario generator should integrate information about the uncertainty, variability, and correlational structure of the input parameters. Using an appropriate sampling method (e.g., Monte Carlo method), a set of any given number of fire scenarios may be constructed. This distribution of scenarios generated will contain the typical cases as well as the worst-case scenarios in the tails of the distribution. The steps involved in developing a distribution of design fire scenarios are (a) selecting a calculation procedure; (b) identifying the uncertain and crucial input parameters; (c) generating a distribution of design fire curves; (d) defining distributions of and modeling correlations among input parameters; and (e) selecting a sampling method and determining the number of scenarios.

### Step 5a: Select Calculation Procedure(s)

There are a range of calculation tools and models currently available from which to select the calculation procedure(s) to be used in the performance-based design. The Fire Protection *Handbook* provides a good overview of the various types of fire models.[38] Which model or type of model is selected depends on several factors, including the application of interest. Fire models can be used to predict a hazard, predict a risk, reconstruct a fire, interpolate between or extrapolate beyond test results, or evaluate a parametric variation. The application of fire models for each of these purposes is discussed by Nelson.[39] Each of these applications may have purpose at some stage of the performance-based design process.

### Step 5b: Identify Uncertain and Crucial Input Parameters

Once a calculation procedure is chosen and candidate designs have been selected, the input parameters necessary for the calculation are evaluated. Which input parameters will be treated as uncertain must be determined. Ideally, only parameters or combinations of parameters with uncertainty great enough to change decisions regarding the final design are treated as uncertain. These are referred to as the crucial variables. Unfortunately, we do not always know a priori which of the input parameters possess crucial uncertainty. Therefore, we must use a combination of judgment and results of previous analyses. The uncertainty importance of each of the uncertain input parameters is determined so that future analyses may be simplified. Eventually, only a few key parameters may be needed to capture the uncertainty in each calculation.

### Step 5c: Generate a Distribution of Design Fires

Design fire scenarios are made up of both possible fire events (heat-release rate curves) and characteristics of the material burning, of the building, and other relevant information such as weather conditions. A set of design fires is established to mimic the type and frequency of fires expected for that occupancy. These design fire curves are based on statistically collected data, judgments, and the goals of the design. Each design fire is assigned a likelihood of occurrence.

### Step 5d: Define Distributions of and Correlations among Other Inputs

The uncertainty and variability surrounding each variable must be captured in the mathematical description of that variable. Any and all available knowledge regarding the value of that parameter should be incorporated into the input scenario generator. This includes empirically measured values, known variations, and statistically compiled data. For example, for a given occupancy type, the NFPA publishes statistical data on the percentage of fires that start in each potential room of fire origin. This information should be incorporated into the random scenario generator so that the generator mimics these statistics. Distributions can be constructed for variables such as temperature, wind, and relative humidity from regional data published by the national weather service data. Methods for quantifying measurement uncertainty* are used to capture uncertainty and variability in empirically measured parameters such as rates of production of products of combustion. In many cases, where hard data do not exist and are not possible to create, expert elicitation is needed to quantify the uncertainty.

When two or more variables are correlated, knowledge of the value of one variable tells one something about the value of the other variable(s). Correlation among variables is modeled so that the input scenario generator will not generate unrealistic scenarios. For example, if the design incorporated a weather module, a month of the year would be randomly selected. For that given month, a value is sampled from an outdoor temperature distribution based on National Weather Service data for that region. Outdoor temperature is correlated to external pressure, wind, relative humidity, likelihood of windows/doors being open, indoor temperature and pressure, and initial fuel temperature. This prevents the software from generating, for example, a scenario where there is a fire on a below-freezing day in August, in California, and all the windows are open.

### Step 5e: Select Sampling Method and Determine Number of Scenarios

**A** sampling method, such as Monte Carlo, Latin Hypercube, or quasi-random must be selected. By sampling a single value from each of the distributions in the input scenario generator and combining those numbers with the values of input parameters that are being treated as certain, any number of independent fire scenarios may be generated.

**A** large number of scenarios increases the statistical significance of the results. However, this relationship is dependent on the sampling method chosen and is not linear. Using 2000 runs may not provide any more insight than using 500. The number of scenarios chosen depends on (1) the number of uncertain input parameters, *(2)* the average calculation time per scenario for the calculation procedure chosen, and **(3)** the statistical significance needed. When conducting correlational analyses between inputs and outputs, one obtains importance or correlation coefficients, $c$, between 0 and 1. Hald provides a formula for determining the relationship between the number of runs, $n$, and the statistical significance (as measured by a t-test) of the correlation coefficient.[40]

$$t = \frac{c}{\sqrt{1-c^2}}\left(\sqrt{n-2}\right)$$

The value for $t$ is related to the confidence level, which is typically chosen as 95 percent.

### Step 6: Develop Candidate Designs

The candidate design is intended to meet the project requirements. **A** candidate design includes proposed fire protection systems, construction features, and operations that are provided in order to meet the performance criteria when evaluated using the design fire scenarios.

### Step 7: Evaluating Candidate Designs—Introduction

Each candidate design must be evaluated using each design fire scenario. The evaluations indicate whether the candidate design will meet the elements of the probabilistic statements of performance. Only candidate designs that meet the performance criteria may be considered as final design proposals. Without the quantitative treatment of uncertainties in the design, each calculation will provide a point estimate only of the important outcome criteria. For example the performance criteria for a design may be a 100°C maximum temperature reached in the upper layer. The time to an upper-layer temperature of 100°C may be predicted as 175 s, and the time to activation of a sprinkler may be predicted as 171.2 s by a given computer model. Because the sprinkler is predicted to activate before the performance criteria is exceeded, this would be deemed an acceptable design. However, the uncertainty in the prediction of time to 100°C may be $\pm 20$ s. This would mean that the temperature in the room may reach 100°C at 155 s or before activation of the sprinkler. Also, the predicted time to activation of the sprinkler has an uncertainty surrounding it as does the temperature at which untenability might actually occur.

The performance-based design process with uncertainty will aid in the calculation of a range of possible values for each key outcome criterion instead of a single point value. This methodology is useful for and may need to be applied to several parts of the design calculations. For example, it could be applied to the calculation of upper-layer temperatures, to the prediction of time to response of devices, and to the prediction of time needed to egress a building.

### Step 7a: Calculate a Set of Values for Each Outcome Criterion

**A** single value will be determined for each outcome criterion calculated for each design fire scenario run. Much information can be obtained from observation of both the range of values for criteria of interest and from cumulative distribution functions generated from the set of all values.

If criteria are time-series values, each scenario will predict a different curve of the key outcome criteria versus time. For example, if upper-layer temperature is the criterion of interest, four design fire scenarios would produce four curves of upper-layer temperature versus time.

Figure 5-4.2 shows a representative graph of the value of outcome criterion A plotted against time from ignition (in seconds). For any given design, there will be as many curves as there are design fire scenarios calculated. One can see that the curves vary both in the magnitude of the peak value and in the time to the peak value.

The range of values predicted from the set of design fire scenarios represents the uncertainty in the value of the outcome criterion. From the set of predicted values of a single outcome criterion, a cumulative distribution function may be generated. This is done by graphing the value of the criterion against its rank order. For example, for $n$ design fire scenarios, $n$ values of a given criterion are generated. These values are then sorted in descending order. The largest value is graphed versus $1/n$, the second largest against $2/n, \ldots,$ and the smallest value against $n/n$ or 1.

An example of a cumulative distribution function (CDF) is shown in Figure 5-4.3. The time to reach a threshold value of 1 or more of the tenability criteria, that is, a value determined to cause injury or death, can be determined from the time-series predictions. The threshold value may be a particular temperature or carbon monoxide level or a parameter used to represent some synergistic effect of a combination of the tenability variables. One value of time to untenability is obtained for each scenario run. The set of all possible values provides a distribution of the outcome criteria.

Figure 5-4.3 shows that for the distribution of design fire scenarios, there is almost a 1.0 probability that the time to a critical value of criterion A is 30 s or more. Likewise, there is a 0.75 probability that the time to this value is 120 s or more, a 0.50 probability that it is 180 s or more, and a 0.1 probability that it is 390 s or more.

### Step 7b: Determine Sensitivity of Outcome Criteria to Elements of Probabilistic Statement of Performance

The sensitivity of key outcome criteria to each of the four elements of the probabilistic statement of performance upon which a design is judged must be known before good policy and good design practice can be established. Elements such as criteria, threshold values, probabilities, and times are not mandated nor agreed upon by fire safety and health professionals, nor the public. Therefore, major conclusions of all designs should be checked in order to demonstrate the sensitivity to uncertainty in each of these elements. This might include checking for times to untenable temperature, carbon monoxide, carbon dioxide, and reduction in oxygen. It may include checking for synergistic effects of the presence of these substances. It may also be appropriate to evaluate for heat flux and visibility.

The same design may be judged on two different performance criteria or by two different critical values of the same performance criterion. Figure 5-4.4 shows an example of time to untenability based on different values of upper-layer temperature. This type of presentation could also be used to determine the effect on time to untenability by selecting a group of tenability criteria or by including different sets of components in the specification of tenability criteria.

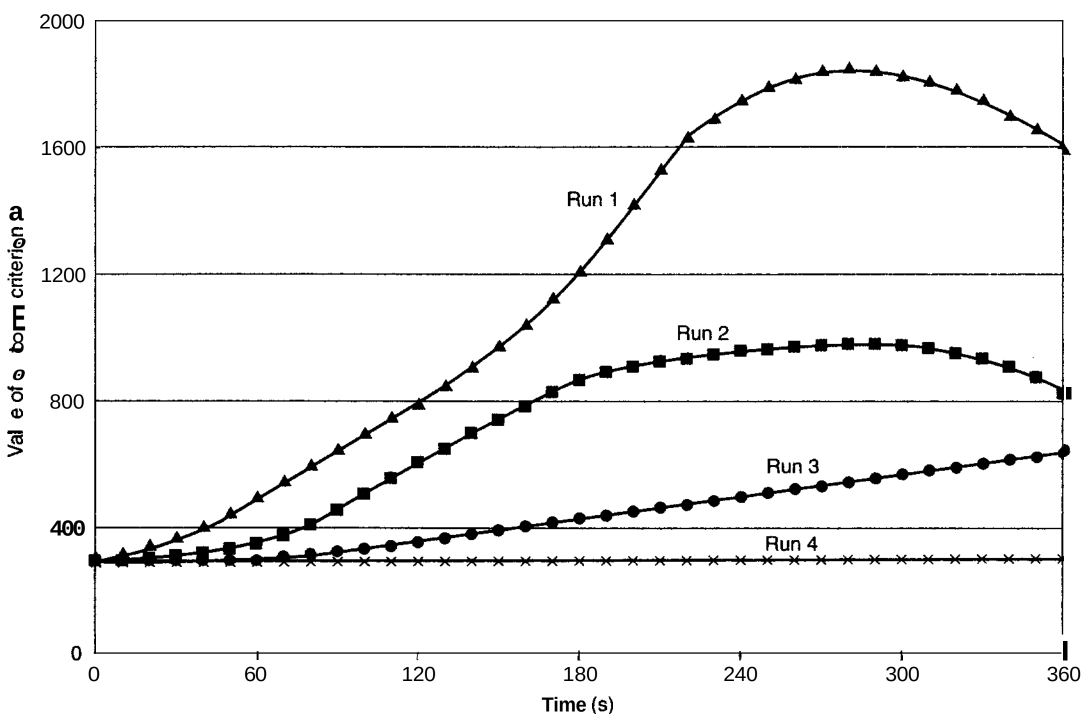


**Figure 5-4.2.** ***Variation in prediction of time-series values of outcome criterion A.***

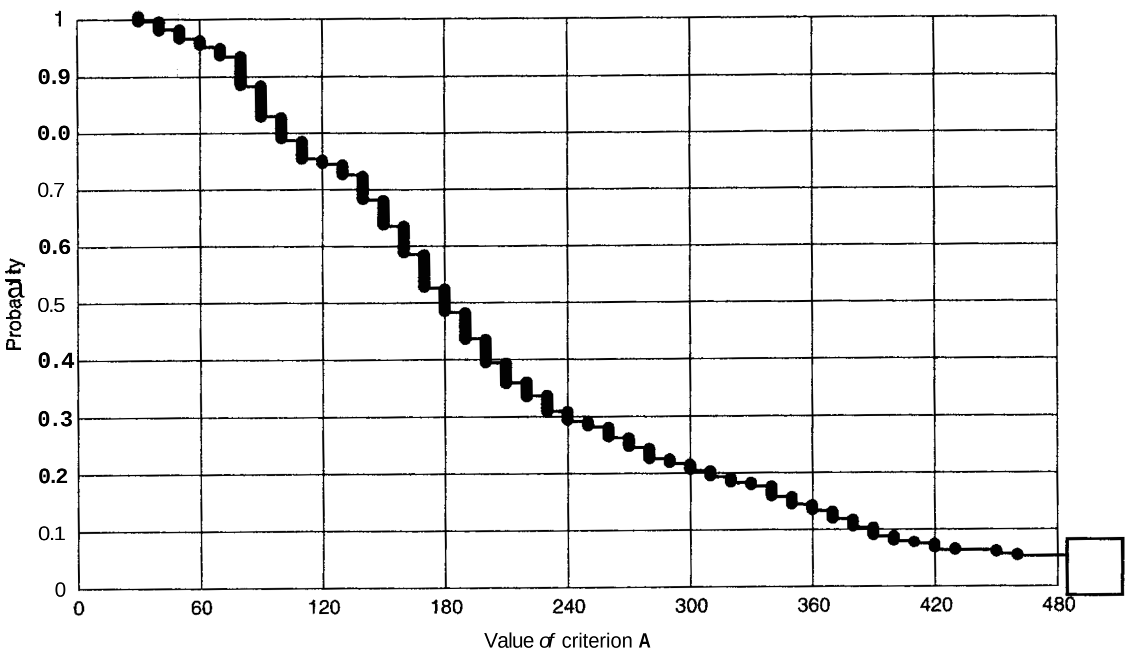


**Figure 5-4.3.** ***Cumulative distribution function of time to the critical value of criterion A.***

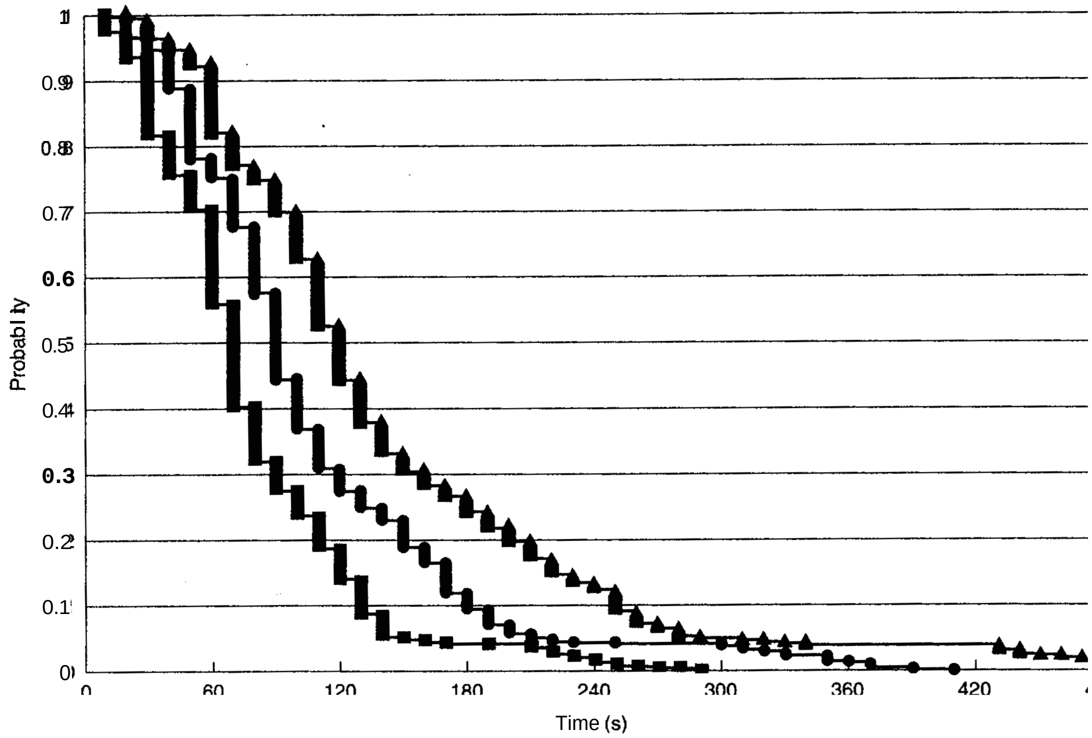


**Figure 5-4.4.** ***Probability of having X seconds or more before untenable upper-layer temperatures are reached for three different values of untenable temperature.***

This type of evaluation is a good way to focus discussions among stakeholders on deciding which tenability criteria should be included, what effect the selection of different threshold values of tenability criteria has, what probability level is acceptable to the stakeholders, and how to select the final design. **At** the end of this step, final performance criteria must be selected for use in judging acceptability of designs and choosing a final design.

### Step 7c: Evaluate Base Case

Depending upon the needs and the scope of the project, it is helpful to compare a candidate design to a base-case design. The base case can be the design that meets the prescriptive code, the design that includes the fire protection options currently in the building, or the design with no active fire suppression systems. The purpose of having a base case is to benchmark the effects of fire on the building and on the building conditions against each of the designs.

In Figure 5-4.5, the results of multiple scenario runs are used to show the probability of safe egress graphed against the time to untenable conditions for two different designs. Design 1 and Design 2 may represent two different performance designs or a performance design and a prescriptive design. Reiss discusses the need for this comparative approach.[41] The graph shows two design curves that exhibit crossover. Design 1 provides a higher probability of tenability out to 50 s; however, Design 2 provides a higher probability of tenability at longer times.

Another way that the acceptability of a design is judged is by comparison of the level of safety provided to that provided by the corresponding prescriptive design. There is uncertainty associated with the prescriptive design also. The prescriptive code will mandate certain building materials and fire detection and suppression schemes. However, uncertainty and variability remain in the weather, ventilation conditions, human behavioral aspects, and where and how the fire will start. Thus, multiple scenarios can be constructed in a parallel manner to that shown above, holding as constants those factors required by the prescriptive code. Thus, a CDF for the prescriptive code can be generated and compared to the CDF for the performance code.

### Step 7d: Determine the Effect of Each Candidate Design on Each of the Scenarios

To compare two different candidate designs, we may want to look at the distribution of differences between the two designs based on the final selected performance criteria. One may consider differences between a design and the reference base case or differences in time to untenability provided by Design 1 versus Design 2. For example, Figure 5-4.6 is a cumulative distribution function of the difference in time to untenability provided by Design 1 minus the time to untenability provided by Design 2.

Figure 5-4.6 shows that there is a 0.25 probability that Design 1 will provide a longer time to untenable conditions than will Design 2. Conversely, there is a 0.75 probability that Design 2 will provide a longer time to untenability than will Design 1 and a 0.25 probability that the difference will be 100s or more better. In selecting a final design, it may be helpful to investigate what factors might lead to Design 1 providing more time to untenability than Design 2, which could highlight ways to improve the design.

### Step 7e: Evaluate Uncertainty Importance

An importance analysis is a particular type of sensitivity analysis that determines which of the uncertain input variables contributes most to the uncertainty in the outcome variable. The results are used to simplify future performance-based designs by identifying the one or two, or small group of, most important inputs. Importance here is measured by the correlation between the output value and each uncertain input. Each variable's importance is calculated on a scale from 0 to 1 (or –1). A correla-

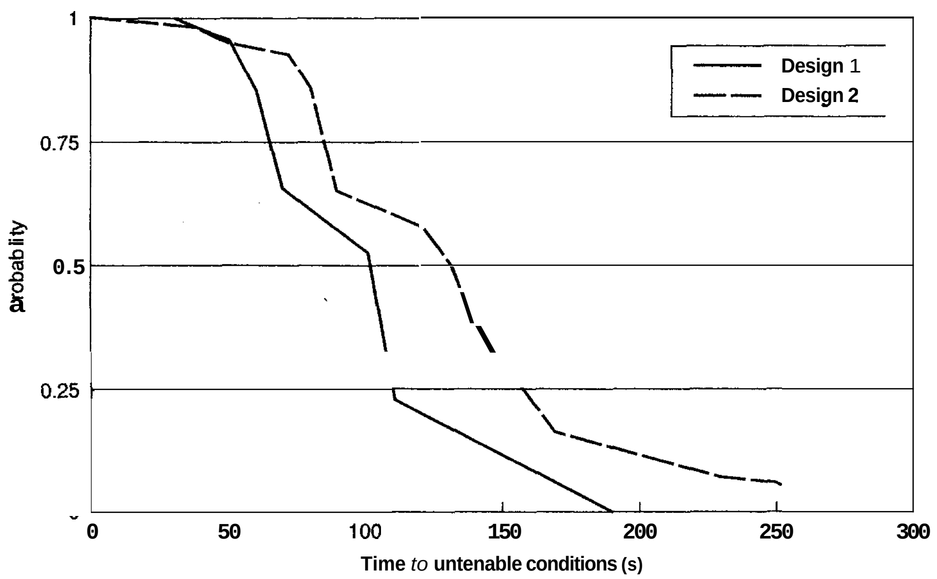


**Figure 5-4.5.** ***Comparison of cumulative distribution functions of time to untenable conditions for two different designs.***

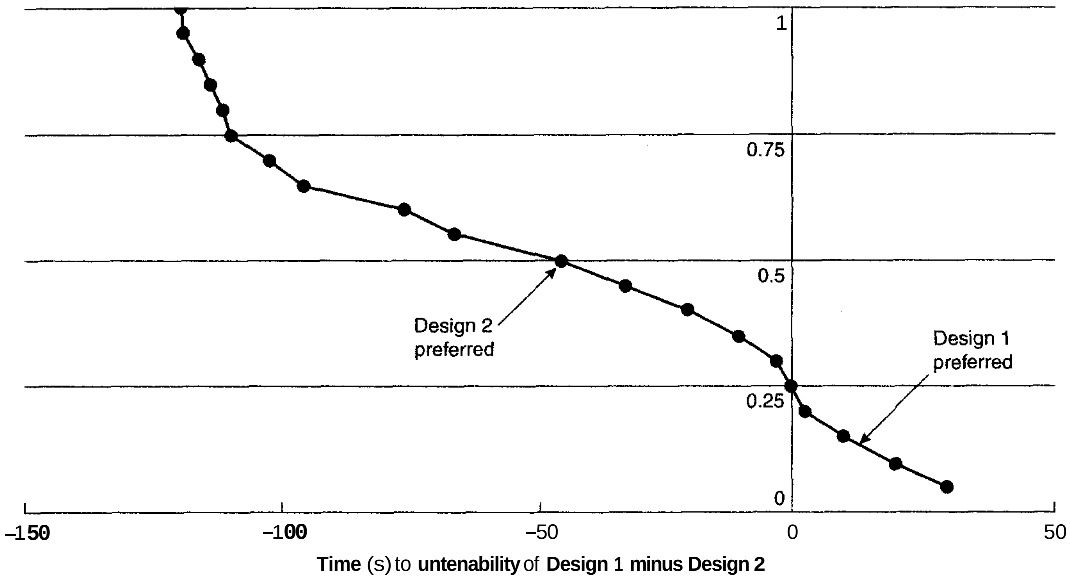


*Figure 5-4.6. Cumulative distribution function of time to untenability of Design 1 − Design 2.*

tion of 0 indicates that uncertainty in the input variable has no effect on the uncertainty in the output parameter. The input parameters can be correlated to composite or derived outcomes (i.e., an outcome that is not directly an output of the model but one that is derived from the output data). Likewise, input variables can be combined (for example, the volume of a room can be determined from the dimension). Room volume may be correlated with key outcome criteria, for example, peak temperature or time to peak temperature.

Importance analysis can be used to simplify a future uncertainty analysis by determining the input uncertainties that are most crucial. This can simplify the process for a class of buildings and can demonstrate where additional research would be effective in reducing uncertainty and ensuring a safer, more predictable building. It must be remembered, however, that correlation does not equal causation. Thus, any apparent, strong correlation that is counterintuitive should be investigated with good engineering judgment. Also, for each design, the value of the correlation coefficient that is statistically significant will depend on the number of scenarios run and the sampling method used.

### Step 8: Judging a Design's Acceptability Based on All Four Elements of Probabilistic Statement of Performance

There are two ways to judge acceptability of a design. The first is based on the minimum time to untenability anywhere in the building, including the room of origin. The second is the time to untenability along the egress path. In general, for both cases, cumulative distribution functions are used to judge acceptability of a design. For example, Figure 5-4.3 is a cumulative distribution function of the time to a specific value of criterion A in the room of origin. If the probabilistic statement of performance required a 0.9 probability of having 30 s or more before reaching this value, it can be determined from the CDF that this criterion is met. In fact, Figure 5-4.3 shows that there is a 0.9 probability of having 80 s or more. However, if the probabilistic statement of performance requires a 1.0 probability of having 50 s or more, Figure 5-4.3 shows that this criterion is not met because the CDF demonstrates a 1.0 probability of having only 30 s or more.

Another way of judging the acceptability of a performance-based design is with a time-to-egress analysis. The time needed to egress a building is often represented in the literature as the time to detect the fire, plus the time to react, plus the time to travel to a safe place. This is represented mathematically as

$$time_{\text{egress}} < time_{\text{untenability}}$$
$$time_{\text{egress}} = time_{\text{detect}} + time_{\text{react}} + time_{\text{travel}}$$

One problem with this approach is that it is very difficult to predict human behavior in terms of reaction time and travel time during a fire. There is both variability due to age and health of the individual and uncertainty as to individual goals and concerns (e.g., will the person try to fight the fire, locate valuables, rescue pets, or notify other occupants about the fire?). The methodology described in this chapter may be applied to egress calculations; however, since these are difficult to predict, it is suggested that perhaps these are best handled as societal and policy decisions. Regulatory decisions may be made as to the available, safe egress time. For example, more time may be mandated for a healthcare facility, where patients may be nonambulatory and/or asleep at the time of the fire, than in an office building where occupants are generally awake and healthy.

### Steps 9–10 Select Final Design and Prepare Documentation

Candidate designs that satisfy the probabilistic design statement(s) may be considered for selection as the final design. When more than one candidate design meets all four elements of the probabilistic statement of performance, other factors such as cost and preference are considered. When considering multiple designs or designs with very different features, a multicriteria decision analysis model may be developed to aid in selecting the final design.

Proper documentation of a performance design is critical and should be written so that all parties involved understand what is necessary for the design implementation, maintenance, and continuity of the fire protection design. *The SFPE Engineering Guide to Performance-Based Fire Protection Analysis and Design of Buildings* suggests that the documentation have four parts: the fire protection engineering design brief, the performance design report, the detailed specifications and drawings, and the building operations and maintenance manual.[11] It is important that the performance-based design report convey the expected hazards, risks, and performance over the entire building life. It should include the project scope, goal, and objectives, the probabilistic design statements, a discussion of the design fires and design fire scenarios, and any critical design assumptions.

### Treatment of Uncertainty

In conclusion, incorporating uncertainty in a fire safety engineering design calculation aids in ensuring performance. The methodology described in the above section can be used in combination with standard performance-based design procedure. Each step in the methodology may be expanded or contracted to fit the needs of a given calculation. In the future, one may be able to construct libraries of models with families of input scenario generators and develop reusable models for classes of buildings. Ultimately, a fire safety engineering model should be developed that directly incorporates uncertainty.

## Application of Uncertainty to Cost-Benefit Models and Decision Analysis Models

### Decision Making under Uncertainty

The importance of making good decisions under conditions of uncertainty is becoming better understood in many fields, including fire safety design. The recently released National Science Policy study, "Unlocking Our Future: Toward a New National Science Policy," states that "decision makers must recognize that uncertainty is a fundamental aspect of the scientific process." Good decisions can be made under uncertain conditions; however, one must capture the nature and magnitude of the uncertainty in order to make a good decision.[42]

There is uncertainty involved in deciding among fire safety options, such as whether to install smoke detectors, sprinklers, or both, Another example is deciding whether the cost of redundant pumps or entire redundant systems is justified. These types of decisions are typically modeled using fire safety trees.[43] However, average or best-guess estimates typically are used for parameters in the decision model, and uncertainty and variability in these are rarely considered.

Decisions made by municipalities on whether to mandate fire safety systems, such as residential sprinklers, are likewise often made based on economic analyses using best-guess and national average values. Integration of uncertainty and variability into these types of cost-benefit studies would provide the decision maker more insights into the issues at hand. It would also highlight where engineering technology is able to reduce risks and where regulatory solutions might be more helpful.

This is becoming more complex because implementation of any form of a performance-based standard will require more decisions to be made. These decisions will be more difficult, more complex, and more uncertain than under a prescriptive-based code. Robert Clemen discusses in his book, *Making Hard Decisions,* four reasons why making decisions is so difficult.[44]

- *First, decisions can be difficult simply because of their complexity* In the case of decisions regarding fire protection features, one must consider the potential for property protection, life safety, injury mitigation, and business continuity. One must also consider the diverse impacts on people with special needs, such as the very young, the elderly, or persons with limited mobility.
- *Second, decisions can be difficult because the decision maker may be working toward multiple or competing objectives.* In fire protection analyses, typically competing objectives are low cost and high level of safety. Progress in one direction, such as installing automatic fire sprinklers for increased fire safety, may impede progress of a competing objective, such as designing an economical building.
- *Third, a problem may bc difficult if different perspectives lead to different conclusions.* h a fire protection decision, the perspective of the building owner, designer, and authority having jurisdiction may very well differ.
- *Finally, decisions can also be difficult because of the inherent uncertainty.* Uncertainties may arise in the model physics, the values of the inputs, the reliability of the devices, and the frequency of events. Yet a decision must be made without knowing for sure what these uncertain values will be. In fact, the most important decisions are often those that must be made under the greatest uncertainty, have the highest complexity, and involve multiple perspectives and goods.

The quantitative treatment of variability and uncertainty using the tools and techniques presented earlier in this chapter can help in identifying important sources of uncertainty and representing that uncertainty in a quantitative way.

The following section introduces an analytical approach that allows quantitative models and decisions models to be built with the integrated treatment of uncertainty. The final section demonstrates how these tools were used in a cost-benefit model of the decision to mandate residential fire sprinklers from a municipal standpoint.

### Available Software That Incorporates Uncertainty

Decision analysis applications often use generic modeling software such as spreadsheets, statistics packages, and financial modeling languages. Specialized software is also available for modeling decision problems using decision trees, influence diagrams, belief networks, multiattribute utility functions, hierarchical value structures, Monte Carlo simulation, and multicriteria optimization.

Two such pieces of software that allow for direct treatment of uncertainty are Analytica"' by Lumina and @Risk™ by Palisade. These are just two software options. They are described here for informational purposes only, intended to provide the reader with an idea of the capabilities of currently available software. The reader is encouraged to evaluate the full range of available software before selecting a package.

@RISK is a risk analysis and simulation add-in for Microsoft Excel or Lotus 1-2-3. @RISK adds the power of Monte Carlo simulation to your spreadsheet models. It allows the user to replace uncertain values in their spreadsheet with probability functions, which represent a range of possible values. @RISK will recalculate your spreadsheet hundreds or even thousands of times, each time selecting random numbers from the functions entered. The result is distributions of possible outcomes and the probabilities of getting those results. This identifies not only what could happen in a given situation, but how likely it is that it will happen.

Analytica is another program that allows for the direct treatment of uncertainty. A model built in Analytica uses a graphical interface that resembles an influence diagram. This diagram conveys the model structure. **A** complicated model can be easily organized into a hierarchy of comprehensible and simple modules. The influence diagram format easily distinguishes between decision variables (those you can control), chance variables (uncertain quantities that cannot be controlled), and objectives (criteria to maximize).

Other distinctive features of Analytica are what the company terms *intelligent arrays* and also turn-key importance analysis. With intelligent arrays, data may be entered as an array indexed by several parameters. The software handles operations on these multidimensional values, such as adding, multiplying element by element, or summing over a dimension. Examples of intelligent arrays are presented in the following section.

In Analytica uncertainty can be treated explicitly with probabilities. The user can express uncertainty about any variable, selecting a probability distribution using a graphical browser; propagate uncertainties with the model using Monte Carlo sampling; and display uncertain results as standard statistics, probability bands, probability density functions, or cumulative probability functions. Analytica conducts rank-order and importance analyses. These tools help one decide which uncertainties make a difference to help determine whether getting better data or expanding the model is worthwhile. Analytica also allows for parametric analysis by graphing model behavior as one or more inputs are varied.

### Example of Cost-Benefit Model with Variability and Uncertainty

In the United States, approximately 3500 people die each year in residential fires. The number of residential fire deaths, however, varies with the type of housing, area of the country, and community size. The cost of installing residential fire sprinklers varies with areas of the country and house age. Thus, the true cost-benefit will be different for each combination of the above parameters. However, cost-benefit models typically use average costs and probabilities and do not incorporate uncertainty.

**A** model was built using Analytica that incorporated variability and uncertainty to determine the societal benefits and costs of mandating residential sprinklers. A full description of the mathematical model and the results is beyond the scope of this chapter but can be found in "**A** Municipal Model of the Cost of Mandating Residential Sprinklers."[45] **A** brief overview of that study is presented in order to demonstrate the techniques used in the treatment of variability and uncertainty and the implications for fire protection analyses.

### Treatment of Variability and Uncertainty

Interyear variability in fire loss statistics: To conduct a cost-benefit study of residential fire sprinkler systems, many fire statistics (e.g., death rates, injury rates, and average direct dollar losses) are needed as inputs. National average values of these numbers are often used in these analyses. For example, the national average value for the residential death rate would be equal to the number of residential fire deaths nationally divided by the number of occupied residential units. The actual fire death rate will vary with a number of parameters.

The U.S. National Fire Protection Association publishes death rates discretized by three of four index variables: region of the country, community size, and house type.[46] The fourth index variable, house age, is accounted for in the cost functions as it is more expensive to retrofit sprinklers than it is to install them during the construction phase. There are four regions of the country, eight community sizes, and three house types. Thus, the death rate used in these calculations is a $4 \times 8 \times 3$ matrix consisting of 96 values for death rate. Two examples would be the death rate in mobile homes in a small community (2500 or less) in the South and the death rate in a one- or two-family dwelling in a community size of 25,000 to 50,000 in the West.

Yearly variability in fire loss statistics: It is important to differentiate between variability and uncertainty. Variability in fire statistics from year to year arises because of the randomness of the occurrence of fires. For instance, in one particular year, several large-loss fires may occur followed by few or none the next year. In this study, since there is an interest in benefits and costs over the life of a fire sprinkler system, mean yearly values were chosen. Yearly variance in deaths, injuries, property loss, and indirect losses due to fires is thus accounted for by taking mean yearly values over a five-year period. Mean values were calculated from the 1989–1993 data.

**Uncertainty in the fire statistics:** Uncertainty in fire loss statistics exists due to the impossibility of a full and accurate accounting of all fires and all fire losses. Mathematical techniques are thus used to provide estimates.[47] Uncertainty in the fire data is represented as uncertainty about the mean values. An expert elicitation of the chief statistician of **NFPA** was conducted to set the uncertainty bands for the fire statistics.[48]

**Uncertainty in other (empirical) model inputs:** Uncertainty in the cost data and parameters such as the sprinkler reduction factor were determined by bounding. For example, uncertainty in the sprinkler reduction factor arises because of the small number of fires occurring in homes with automatic sprinklers installed. Data from other occupancies were used to bound the uncertainty.

**Propagation of uncertainty:** Once the uncertainties in the model inputs have been expressed, the question becomes, How can we propagate these uncertainties through the model to discover the uncertainty in the predicted consequences? In this analysis a Monte Carlo simulation was used. A value for each input is randomly selected from its actual probability distribution. From these values, a value for the outcome criteria is calculated. This process is repeated many times, resulting in a probability distribution for each outcome variable.

**Value/cost of death averted** For any cost-benefit analysis regarding health and safety, one of the most highly contentious points is setting a value of life. Economists have come up with various ways of estimating the value of a life. These include willingness to pay for safety devices, and income-based estimates.[49] All these methods are highly debated. For this study, the problem of establishing a value of life was avoided by means of careful selection of the outcome criteria. By selecting the outcome criteria to be dollars per premature death averted and dollars per life-year saved, no explicit value of life needs to be specified.

**Results—national average calculation versus indexed calculations:** When variability due to region, community size, house type, and house age are accounted for, the net cost of residential sprinklers varies tremendously. The net cost for installing residential sprinklers varies by greater than a factor of *35* times. From a low of $1.4 million per premature death averted (for a new mobile home in a small community in the South) to a high of $35.1 million (for a retrofit of a one- and two-family dwelling in a medium-size community in the West). Based on a national average calculation, our model predicts that residential fire sprinklers have a median net cost of $7.3 million dollars per premature death averted.

**Comparison to other lifesaving interventions:** An article in Risk *Analysis* identified over 500 lifesaving interventions, reporting their net cost in terms of dollars per life-year saved.[50] The accuracy of the results is limited by the accuracy of the data and assumptions in each original analysis, but the results are believable within an order of magnitude. In this study the cost per life-year saved for residential fire sprinklers was compared to the cost per life-year saved for chlorination of drinking water, banning urea-formaldehyde insulation in homes, installing oxygen depletion sensors for gas space heaters, conducting radon remediation, mandating child-resistant cigarette lighters, and installing ground fault interrupters. Figure 5-4.7 below shows this comparison. The heights of the bars represent the relative costs per life-year saved and have all been normalized to the cost of chlorination of drinking water.

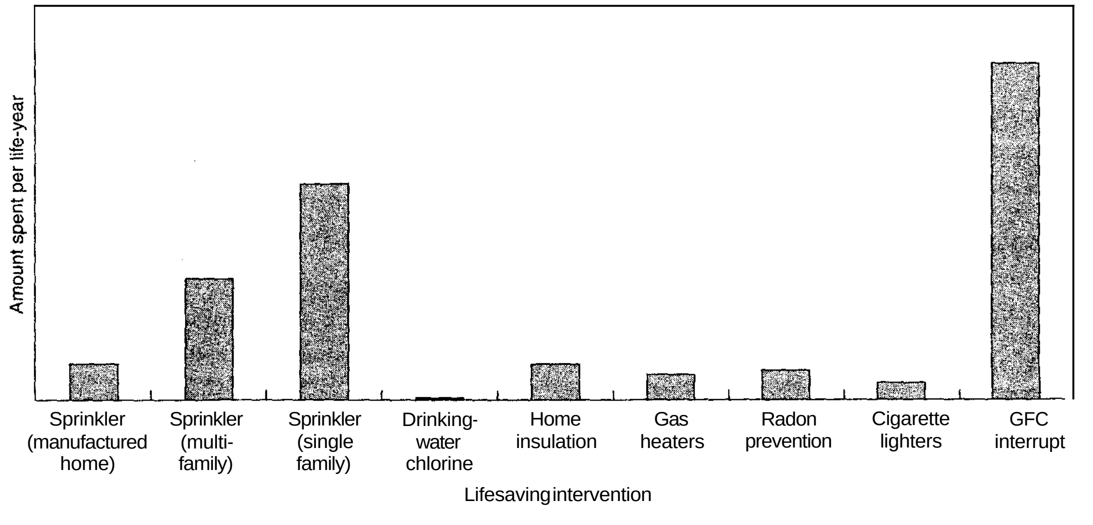


***Figure* 5-4.7. *Comparison of net cost of fire sprinklers in manufactured homes with other residential lifesaving interventions.***

### Uncertainty in Cost-Benefit and Decision Analysis Models

This example demonstrates how uncertainty and variability may be treated in a cost-benefit or decision analysis model. It also showed that effectively treating variability and uncertainty, and use of tools such as importance analysis and comparative analysis, can lead to greater insights. The cost of mandating residential fire sprinklers in new mobile homes was shown to be as low as five times less than the cost of mandating residential fire sprinklers using national average values for fire risk and costs. The cost of mandating residential fire sprinklers in existing single family homes was shown to be up to five times more than using national average numbers. The comparative analysis provides lawmakers a frame of reference by comparing the cost of mandating residential fire sprinklers to the costs of mandating other residential safety options with lifesaving potential.

## Conclusion

The treatment of uncertainty is key to ensuring and maintaining an appropriate level of public safety while allowing the flexibility necessary to reduce costs. This is true for all fire safety engineering calculations, whether conducted to meet a performance-based code, to aid in the establishment of a prescriptive requirement, or to compare a performance option to its prescriptive counterpart. Beyond being just another step in the process of getting a building approved, properly determining and documenting a level of confidence in the design will have numerous benefits. It will facilitate cooperation among stakeholders by increasing the overall understanding of risks and costs.

Distributions of outcomes are a much richer description of what is possible than the typical point value answers. Though stakeholders and/or policy decisions must still determine how much risk to accept, with thorough uncertainty analyses, this decision will be informed and free of the uneasiness that typically surrounds acceptance of a deterministic performance calculation. The information provided in this chapter is intended to help the fire protection community to understand the nature and sources of uncertainty, to aid in the selection of a calculation procedure, to apply a methodology for the treatment of uncertainty, and to incorporate uncertainty into cost-benefit models and decisions.

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